UNIVERSIDAD CARLOS III DE MADRID working papers

Working Paper 13-05
Statistics and Econometrics Series 04
March 2013

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# Correlations between oil and stock markets: A wavelet-based approach

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***Keywords:*** Correlations; Financial shocks; International Financial Markets; Oil shocks; Stock Market Returns; Wavelets.

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# Correlations between oil and stock markets: A wavelet-based approach*

**Belén Martín-Barragán**[†] **Sofia Ramos**[‡] **Helena Veiga**[§]

**ABSTRACT**

In a global economy, shocks occurring in one market can spill over to other markets. This paper investigates the impact of oil shocks and stock markets crashes on correlations between stock and oil markets. We test changes in correlations at different scales with non-overlapping confidence intervals based on estimated wavelet correlations. Contrary to other approaches, this method does not need adjustment for heteroskedasticity biases on the correlation coefficients. Our results show that oil shocks affect the correlation between both markets. The evidence on the change of correlation between stock markets after an oil shock is weaker; except in some specific cases during the Kuwait war and the OPEC cutback period. Conversely, we only find weak evidence that stock market crashes change the correlation between oil and stock markets. Overall, the evidence gives support to including oil as an asset class in asset allocation strategies.

**JEL classification**: C40; E32; G15; F30

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*The authors acknowledge financial support from Financial Research Center–UNIDE and from the Spanish Ministry of Education and Science, research projects MTM2010-17323, ECO2011-25706, ECO2012-32401 and MTM2012-36163-C06-03.

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# I. Introduction

The keystone of both portfolio allocation and risk management decisions is the correlation structure of security returns. Therefore, modelling the dynamics of correlations remains an important task not only for financial research but also for applications in the financial industry. Financial literature showed the time varying nature of correlations (see e.g. Cai et al., 2009; De Santis and Gerard, 1997; Shawky et al., 1997; Longin and Solnik, 1995, 2001) and has investigated whether stock market crashes or currency crises impact the correlations between international stock markets. Crashes create price shifts in the same direction in many markets, which produces a high correlation between previously uncorrelated markets.[1] King and Wadhwani (1990) examines whether there was a change in correlation coefficients between Japanese, the U.K., and the U.S. stock markets before and after the stock market crash of 1987. They find a significant increase in the coefficients after the crash. In an influential study, Forbes and Rigobon (2002) note that heteroskedasticity biases contagion tests based on correlation coefficients. They show that it is not appropriate to look at unadjusted correlation coefficients as the computed correlation coefficient is an increasing function of the variance of the underlying asset return, so that when coefficients between a tranquil period and a crisis period are compared, the coefficient in the crisis period is biased upwards as volatility rises substantially. However, Corsetti et al. (2005) argue that this finding is a result of an assumed underlying unrealistic model and Bartram and Wang (2005) report that these biases come from the assumptions of the analysis. Hence, when model-free correlation estimators are used, adjustments are not needed.

This work focuses on the correlation structure between oil and stock markets. Energy is a strategic commodity used as an input in all economic activities, therefore, turmoils in the oil market can affect stock returns as well as stock market linkages due to the worldwide energy dependence.[2] Moreover, if stock markets are bellwethers of the economy (Fama, 1990; Fama and

[1]See Kabir and Hassan (2005) for a discussion on how the Russian default generated losses for the LTCM hedge fund.

[2]More about the link between economic recessions and oil prices we refer the reader to the seminal paper of Hamilton (1983).

French, 1989; Schwert, 1990), dramatic changes in stock prices can betoken future macroeconomic changes that might affect oil demand. We investigate whether oil price shocks and stock market crashes have an impact on stock market and oil market correlations. Differently from works of Huang et al. (1996); Chen et al. (1986); Jones and Kaul (1996); Driesprong et al. (2008); Ramos and Veiga (2012), the focus of our work is not on the direct impact of oil shocks in stocks market returns, but on the impact on the correlation structure between those markets.

To analyze this issue, we follow recent works that propose to use different frequency levels to distinguish between contagion and interdependence. Bodart and Candelon (2009) work in the framework of a Vector Autoregressive (VAR) model and propose a contagion test based on a causality measure applied at different frequencies. Orlov (2009) uses the finite Fourier transform without assuming any model for the data. Fourier's analysis allows a decomposition of the covariance into different frequency levels. Contagion is estimated as the change of the high-frequency components of the covariance between crisis and noncrisis periods. Gallegati (2012) identifies contagion and interdependence during the U.S. subprime crisis of 2007 through wavelet decomposition of the original returns series. He advocates that the multi-resolution decomposition property of the wavelet transform can be used to separately identify contagion and interdependence by associating each to its corresponding frequency component. He proposes using the information of the high frequency part to test for contagion, while the low frequency component could be used to analyse interdependence.

The work is developed as follows. We analyze the impact of sharp oil increases during the 1990-2011 period, e.g., those in Kuwait and Iraq wars, the OPEC cutback in 1999 and the peak of oil in July 2008 on four stock markets indexes: Germany, Japan, the U.K. and the U.S.. Next, we test for contagion between oil and stock markets, but also for contagion between stock markets given an oil price shock, i.e., if between international stock markets correlation changes significantly during a period of turbulence of oil markets. Finally, we also analyze the impact of stock market crashes in the correlation structure of oil and stock markets.

In order to deal with all these issues, wavelets are used as the main methodology. The wavelet methodology is appropriate because it allows a time series to be decomposed into different frequency components that extract the short-term behavior and the low-frequency components which capture the more long-term dynamics of a variable.

Moreover, we use the methodology of Gallegati (2012) based on wavelets to test for contagion between oil and stock markets and within stock markets given an oil shock. The test is graphical, based on non-overlapping confidence intervals of estimated wavelet coefficients calculated in shock and non-shock periods. We present the results with a new visualization tool, where the confidence intervals of different periods are shown along the time line. The plot easily represents the changes of correlation over time and allow us to test for contagion in a given shock period by visually checking the overlap among two consecutive periods.

Our main findings are as follows. In periods without shocks, correlation between oil and stock markets tends to be close to zero or slightly positive. Oil shocks like those caused by the Kuwait and Iraq wars, spill over to stock markets, and change the correlation between oil and stock markets, which becomes negative. The year of 2008 is characterized by a rise in oil prices which peaks in July 2008; but the aftermath of the crisis is distinguished from the other periods of rises because correlation between oil and stock markets is positive. Like Huang (2011), we find that different wavelet details can capture distinct information; however, the four day frequency captures the majority of changes of correlation between oil and stock markets, while the one day frequency only indicates significant changes in correlations, for some stock markets, around the Kuwait war and the 2008 oil peak. The evidence on the change of correlation between stock markets after an oil shock is weaker since the test does not reject the equality of correlations except in some cases during the Kuwait war and the OPEC cutback period. The results also show that the impact of stock market crashes on changes in the correlation structure between oil and stock markets is weak.

To our knowledge, this is the first paper studying the impact of oil shocks and stock market crashes on the correlation structure of stock markets and oil markets. Moreover, our paper contributes to the literature on financial contagion[3] and oil shocks, providing new evidence on the break of correlations between stock and oil markets due to oil shocks and on the impact on stock market linkages, making use of recent methodological developments that overcome heteroscedasticity biases.

The study provides useful implications for the construction of portfolio diversification strategies. Our work supports including oil as an asset class in portfolios. The results show negative correlations with stock markets in case of oil shocks and that stock market crashes do not seem to affect significantly the correlation structure between oil and stock markets.

The remainder of the paper is organized as follows. Section II explain the details of the methodology used to test changes in correlations. Section III describes the data, presents and analyzes the results. Section IV concludes.

# II. Methodology

The methodology is based on wavelets, which allows the study of time series on a variety of scales (or frequencies), to obtain correlation estimates for different frequencies and consequently to test for contagion between financial markets.[4]

Different definitions of contagion have been used in the literature.[5] We follow Boyer et al. (2006), King and Wadhwani (1990) and Forbes and Rigobon (2002), among others, who define contagion as a significant increase in cross-market linkages after a shock to one country (or a group of countries) and measured by cross-market correlations.

[3]See Forbes (2012) for a recent review on the contagion literature and methodologies.

[4]The wavelets analysis differs from Fourier's analysis because Fourier basis functions are only localized in frequency and wavelets are localized both in frequency, via dilatations, and in time, via translations. Discontinuities and sharp spikes usually require fewer wavelet basis functions than Fourier basis functions do. This sparse representation makes wavelets an excellent tool for data compression and statistical applications.

[5]See Table I of Forbes (2012) for a list of definitions.

## A. Wavelet series decomposition

A time series of financial returns can be decomposed into orthogonal components: the wavelet details $(\mathbf{D_1}, \mathbf{D_2}, ..., \mathbf{D_J})$ and the wavelet smooth $(\mathbf{S_J})$. Let $r_{it}$ be a time series $i$ of financial returns at time $t$. $r_{it}$ can be approximated using the orthogonal wavelet series approximation which contains the wavelet smooth coefficients $v^{r_i}_{J,k}$ and the wavelet detail coefficients $w^{r_i}_{j,k}$, such that:

$$r_{it} = S^{r_i}_J(t) + D^{r_i}_J(t) + D^{r_i}_{J-1}(t), ..., +D^{r_i}_1(t), \tag{1}$$

where $S^{r_i}_J(t) = \sum_k v^{r_i}_{J,k}\phi_{J,k}(t)$, $D^{r_i}_j(t) = \sum_k w^{r_i}_{j,k}\psi_{j,k}(t)$, $\phi_{J,k}(t) = 2^{-J/2}\phi\left(\frac{t-2^J k}{2^J}\right)$ and $\psi_{j,k}(t) = 2^{-j/2}\psi\left(\frac{t-2^j k}{2^j}\right)$ for $j = 1, 2, .., J$. Equation (1) represents the wavelet decomposition of $r_{it}$. As an example, the wavelet decomposition of $r_{it}$, for a level 4 of multiresolution, consists of 4 wavelet details $(D_4(t), D_3(t), ..., D_1(t))$ and a single wavelet smooth $(S_4(t))$. The wavelet smooth captures the low frequency dynamics and the wavelet details the high frequency characteristics of $r_{it}$. The maximum number of scales in this case is $2^4$ which must satisfy $2^4 \leq T$, where $T$ is the number of observations in the sample.

In the literature, there are many mother wavelets that can be used to compute the wavelet transform and the corresponding coefficients. Following Gallegati (2012), we use the Daubechies extremal phase orthogonal wavelets with symmetric-padding boundary conditions (Daubechies, 1992) with length eight since filters with moderate lengths, such as eight, seem to be adequate to capture the main features of financial time series (see Gençay et al., 2001). We use a modification of the Discrete Wavelet Transform (DWT) known as maximal-overlap DWT (MODWT), a stationary wavelet transform, designed to avoid the lack of translation-invariance of DWT (Percival and Walden, 2000). The frequency of the data is daily and like Gallegati (2012) we consider that contagion corresponds to the wavelet details of level 1 (1 day), level 2 (2 days) and level 3 (4 days). Computations have been performed using the *waveslim* package developed by Whitcher for the R statistical package of R Core Team (2012) and the *wavelet toolbox* of MATLAB (2010).

## B. Wavelet–based correlations

In this paper, we are interested in testing for significant changes in the wavelet correlations between international stock markets and oil market and also for changes between pairs of international stock markets. We do this separately for each scale $j$. Consider two periods, for instance the Kuwait War ($I_1$) and the period from the end of the Kuwait War until the OPEC agreement ($I_2$). Let $\rho_j(X,Y)^{I_1}$ and $\rho_j(X,Y)^{I_2}$ be the wavelet correlations of two random variables $(X,Y)$ in these two periods $I_1$ and $I_2$, respectively. The null hypothesis of the test

$$H_0 : \rho_j(X,Y)^{I_1} = \rho_j(X,Y)^{I_2}$$

is rejected at a significance level of 5% if the two confidence intervals for $\rho_j(X,Y)^{I_1}$ and $\rho_j(X,Y)^{I_2}$ at confidence level of 95% are non-overlapping (see Gallegati, 2012; Gençay et al., 2001, 2002). We use the intervals estimators proposed by Whitcher et al. (2000) because they are robust to non-Gaussianity. Let $h(\rho) = \tanh^{-1}(\rho)$, then an approximate $100(1-2p)\%$ Confidence Interval for $\rho_j(X,Y)$ for interval $I$ is

$$\left[\tanh\left\{h^{-1}(\hat{\rho}_j) - \frac{\Phi^{-1}(1-p)}{\sqrt{\hat{N}_j - 3}}\right\}, \tanh\left\{h^{-1}(\hat{\rho}_j) + \frac{\Phi^{-1}(1-p)}{\sqrt{\hat{N}_j - 3}}\right\}\right],$$

where $\hat{N}_j = N_j - L_j$ and $L_j = \lceil (L-2)(1-2^{-j}) \rceil$ is the number of MODWT wavelet coefficients associated with scale $j$, $\Phi^{-1}(p)$ is the $p \times 100$ percentage point for the standard normal distribution and $\hat{\rho}_j$ is the following unbiased estimation of the wavelet correlation at scale $j$:

$$\hat{\rho}_j = \frac{\hat{\gamma}_j^{X,Y}}{\hat{\sigma}_j^X, \hat{\sigma}_j^Y}.$$

The wavelet covariance $\hat{\gamma}_j$ and the wavelet variances $\hat{\sigma}_j$ for interval $I$ can be estimated as

$$\begin{aligned}\hat{\gamma}_j^{X,Y} &= \tilde{N}^{-1}\sum_{k\in\tilde{I}}\tilde{w}_{j,k}^X\tilde{w}_{j,k}^Y \\ \hat{\sigma}_j^X &= \tilde{N}^{-1}\sum_{k\in\tilde{I}}(\tilde{w}_{j,k}^X)^2,\end{aligned}$$

where $\tilde{I}$ is the interval $I$ after removing the times $t$ that are affected by the boundary conditions, $\tilde{N}$ is the length of $\tilde{I}$, and $\tilde{w}_{j,k}^X$ (respectively, $\tilde{w}_{j,k}^Y$) are the detail coefficients of the MODWT decomposition of $r^X$ (resp. $r^Y$) at scale $j$.

In order to simplify the visualization of the different tests, for each pair of series of interest (i.e., for each stock market and oil return, and for each pair of stock market returns) we plot the confidence interval of the wavelet correlation at each scale level $j$ in a set of periods of interest. Let $I_1, I_2, \ldots, I_K$ denote the periods of interest, we propose to jointly visualize the confidence intervals of the wavelet correlation at certain scale $j$ for all the $K$ periods. Each interval is located along the horizontal edge according to the date in the middle of the interval. In this way, testing if the correlation in period $I_r$ is significatively different from that in period $I_s$ would correspond to comparing the intervals obtained in these periods. If the intervals do not overlap, then the correlations are significatively different at that scale $j$. Plotting the intervals over time becomes a useful tool for summarizing and interpreting the test results.

# III. Empirical results

In this section we present the data set and calculate the wavelet multiscale correlations between stock market returns of different countries, and between stock and oil returns. Then, we test for changes in the correlations at different frequencies. Several papers in the literature interpret statistically significant positive changes in the correlations as evidence of contagion (see, for instance, Baig and Goldfajn, 1999; Ellis and Lewis, 2000; Forbes and Rigobon, 2002; King and Wadhwani, 1990). Therefore, we first analyze the impact of oil shocks in the correlations between stock and oil markets; then, given an oil shock, we analyze the impact between stock market correlations. Finally, given a shock in the stock market, we investigate whether there is contagion between oil and stock markets.

## A. Data

The data are the stock market indexes of Germany, Japan, the United Kingdom and the United States, provided by Datastream. Oil prices are from the settlement price of the New York Mercantile Exchange (NYMEX) oil futures contract, the most widely traded futures contract on oil. The underlying asset is the West Texas Intermediate oil, a light crude oil widely used as a current benchmark for U.S. crude production. Indexes are in U.S. dollars and oil prices are in U.S. dollars per barrel ($U/BBL). The sample period runs from February 27, 1990 to November 22, 2011 comprising 5665 daily observations. As is customary in the financial literature, returns are computed as $r_{it} = [\ln(I_{it}) - \ln(I_{it-1})]$, where $I_{it}$ is the stock market index of country $i$ at time $t$.

We define periods where there are oil shocks versus periods without oil shocks. We consider the following oil shocks: the Kuwait war in 1990, the OPEC cutback starting in March 1999, the Iraq war in March 2003 and the peak of oil in July 2008 (see Hamilton, 2013, for a reference in oil shocks). In all these periods there were dramatic changes in the price of oil.

Figures 1 and 2 depict the series of prices and returns for our sample, respectively. Moreover, Figure 3 shows oil prices together with historical oil events. Oil prices peaked in 1990 with the invasion of Kuwait by Iraq, and then dropped. After that, the price of oil did not fluctuate very much until around 2002. The price of $40/BBL was only reached again in October 2004. Then a period of price escalation started. Oil prices went from $50/BBL in 2005 to $100/BBL in 2007, to reach almost $150/BBL in July 2008. As many countries entered in recession, prices continued to slide until the end of 2008, to increase again during 2009. The value in December 2009 was again close to $80/BBL and increased during 2011.

Table I reports the summary statistics of stock market indexes and oil returns. Stock market indexes register positive mean returns during the period, with the exception of Japan. Volatility is lower for the U.S. stock indexes. Oil and stock market returns other than these of Japan display negative skewness. Therefore, the Jarque–Bera test rejects the assumption of Gaussian returns for all stock and oil returns.

In order to compute the correlations and test for contagion, we adjust the data for different time zones[6] by matching the return series of U.S. at time $t$ to the daily return series of Germany, the U.K. and Japan at time $t+1$.[7] We consider that most of the news comes from the U.S., as it is the largest stock market and one of the world's largest oil producers.

## B. Changes in correlations given oil shocks

Figure 4 presents the results of testing changes in the correlations and consequently contagion between the oil market and international stock markets for three frequencies (1, 2 and 4 days).

A statistical change in correlation happens for two consecutive shock and non-shock periods, if the estimated confidence intervals for the correlations between the series of wavelet details of oil returns and the series of wavelet details of stock market returns $i$, where $i \in \{Germany, Japan, U.K., U.S.\}$ do not overlap.

We start by the analysis of one day impact on the correlations (first column of Figure 4). For this frequency, we observe three significant changes in correlations: First, in the Kuwait war period, between the U.S. and the oil markets; the second and the third in the oil peak in July 2008, between the Japanese and the oil market, and between the U.S. and the oil market. We observe that the surge in oil prices leads to negative correlations between stock and oil markets. After these periods, the correlations become positive.

The panels of column two of the same figure depict the estimated confidence intervals for the correlations at the frequency of two days. For this frequency, we observe three changes in the correlation between stock and oil markets. The first and second in the Kuwait war period, between the Japanese and the oil market, and the U.S. and the oil market; the third, during the

[6]Martens and Poon (2001) state that the use of non-synchronous closing prices has led to a downward bias in correlation estimates.

[7]Markwat et al. (2009) use a similar adjustment.

oil peak period, between the U.S. and the oil market. During the Kuwait war, the correlations between the series of wavelet details of the major stock and oil markets are quite negative, meaning that increases in the prices of oil lead to decreases in the returns of international stock markets. For both cases, the estimated confidence intervals do not overlap with the confidence intervals of the period after the shock, where the correlations are almost zero, i.e. the change in correlations is statistically significant. For the last case, correlation becomes positive after the shock and it is statistically different from that of the previous period, since the estimated confidence intervals do not overlap.

Column three of Figure 4 depicts the estimated confidence intervals for correlations at the frequency of 4 days. For this frequency, we observe several changes in the correlation between oil market and the stock markets that correspond to three oil shock periods: the Kuwait war, the Iraq war and the oil peak period. For the first period, the German, Japanese, the U.K. and U.S. stock markets register very negative correlations that are statistically different from those of the following calm period, where the correlations are almost zero. In the second period, there is a change in the correlation between the German, U.K. and U.S. stock markets and the oil market. Once more, the correlations during the Iraq war are very negative and statistically different from those of the following calm period. Finally, in the oil peak period all the correlations between stock markets and oil market are negative and statistically different from those of the calm period, where the correlations are positive. Overall, the results are quite consistent: oil shocks that cause an increase in oil price change the correlations between stock markets and oil returns, making them quite negative and statistically different from those of the non-shock periods. The oil shock related with OPEC cutback in 1999-2000 does not seem to lead to changes in correlations, which may be explained by the Kilian (2009) findings that shocks to the production have a lesser impact in the U.S. economy than shocks caused by precautionary demand.

Therefore, the evidence is consistent with soars in oil prices negatively affecting stock market returns and, for the majority of the stocks markets, the frequency of four days signals the majority of correlation changes. On the other hand, the non-shock periods are in general characterized by positive but small correlations between stock markets and oil returns. The exception is the period after the peak of oil prices that coincided with the aftermath of the subprime financial crisis, where correlation increases.

The next step is to investigate contagion between stock markets once an oil shock occurs. If all stock market returns fall sharply then correlation is expected to increase; the question at stake is whether the change in correlation is statistically significant. We report results for the wavelet detail series of level 3; this was the frequency with which we observed the majority of the changes in correlation in the previous analysis.[8] Looking at Figure 5, we observe three changes in the correlation that correspond to two oil shock periods: the Kuwait war and the OPEC cutback periods. For the first shock, we find contagion between the U.K and Japanese stock markets, and the U.S. and Japanese stock markets. In these cases the correlations are positive and significantly different from those of the calm period, which are also positive but of less magnitude. Finally, for the OPEC cutback period, we observe one change of correlation: between the U.K. and German stock markets.

Summing up, we find a transmission of oil shocks to international stock markets. If the event implies a rise in oil prices, we find a negative impact in correlations between stock and oil markets. This impact can be observable at one day frequency for some stock markets, and the change in correlations is more frequent and intense at the frequency of four days. Finally, oil shocks can intensify correlations between stock markets, in particular for the frequency of four days. Consider the Kuwait war as an example. In this period, the correlations among stock markets generally become more positive and statistically different from those of the following period without oil shocks.

## C. Changes in correlations given financial shocks

It is well documented in the literature that correlations among financial time series of returns are much greater in periods of market turbulence than in periods of non–turbulence (see, among

[8] We also made the analysis for the frequencies 1 and 2 days but we did not observe any significant change in the correlation between stock markets.

others, Ang and Chen, 2002; De Santis and Gerard, 1997; Das and Uppal, 2004; Erb et al., 1994; Longin and Solnik, 2001). Considering the turbulence period caused by financial shocks, we inspect contagion between oil and stock markets given a crash in stock markets.

We considered daily drops in stock market return larger than 5%, which allows important events to be captured such as the Asian Crisis in 1997, the Russian Crisis and the bankruptcy of the 'Long Term Capital Management' in 1998, the dot.com bubble bursting in 2000, the aftermaths of the terrorist attack to U.S. on September 11, 2001, of the bankruptcy of 'Lehman Brothers' in September 2008 and the 'Sovereign Crisis' in 2011.

Figure 6 summarizes the results and shows that there are few statistically significant changes in correlation between stock and oil markets. For the first frequency, we observe a change of correlation between the German stock and oil markets, during the Asian crisis in 1997, where the correlations become negative and significantly different from those of the preceding period which are small but positive. At the frequency of 4 days, breaks can be observed on two different dates. In 1998, there is an increase in correlation between the U.K. and oil that is highly positive and statistically different from those of the subsequent period that are around zero. In 2011, correlations between stock and oil markets are higher than in the preceding calm period. Although only in the cases of Japan and Germany, the difference is statistically significant, the increase in correlations can be observed for the four analyzed countries.

## IV. Conclusions

In a global economy, shocks occurring in one market can affect other markets and change the structural linkages between assets. This paper tests for contagion at different frequencies between oil market and stock markets. The paper uses the methodology of Gallegati (2012) based on wavelets and proposes to jointly visualize the confidence intervals of the estimated wavelet correlations calculated in periods of turbulence and periods of non-turbulence at a certain scale for all the periods. The wavelet methodology is appropriate because it allows a time series to be decomposed into different frequency components that extract the short-term and medium-term dynamics of a variable. Gallegati (2012) argues that the multi-resolution decomposition property of the wavelet transform can be used to separately identify contagion and interdependence by associating each to its corresponding frequency component.

We test for contagion between oil and four large stock markets, Germany, Japan, the U.K. and the U.S.. We focus on changes of correlations due to sharp oil price increases like the Kuwait and Iraq wars, the OPEC cutback in 1999-2000 and the peak of oil in July 2008. The results confirm that oil shocks affect correlations with stock markets. During the shocks, correlations tend to be negative because oil prices increases and stock markets go down, anticipating economic downturns. In non-shock periods, there is an increase in correlations between oil and stock markets that fluctuate around zero. The period after the oil price spike of 2008 is distinguished because correlation between oil and stock markets increases to high positive values. The change of correlation between stock markets related to oil shocks is not so perversive. The Kuwait war changes correlations between the U.K. and the Japanese stock markets, and those of the U.S. and Germany. The OPEC cutback changed correlations between the U.S. and those of the U.K. stock markets, and the U.K. and Germany. Analyzing the effect of stock markets crashes, we find weaker evidence that they affect the correlation between oil and stock markets.

The analysis conducted has a number of implications of interest to policy makers, but also to the construction of optimal portfolio diversification strategies. The results give support to include oil as an asset class in portfolios due to low correlations with stock market indexes and, in case of the oil shocks, it can offer downside protection due to the negative correlation. Moreover, stock market crashes do not seem to affect significantly the correlation structure between oil and stock markets.

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# Figures and Tables

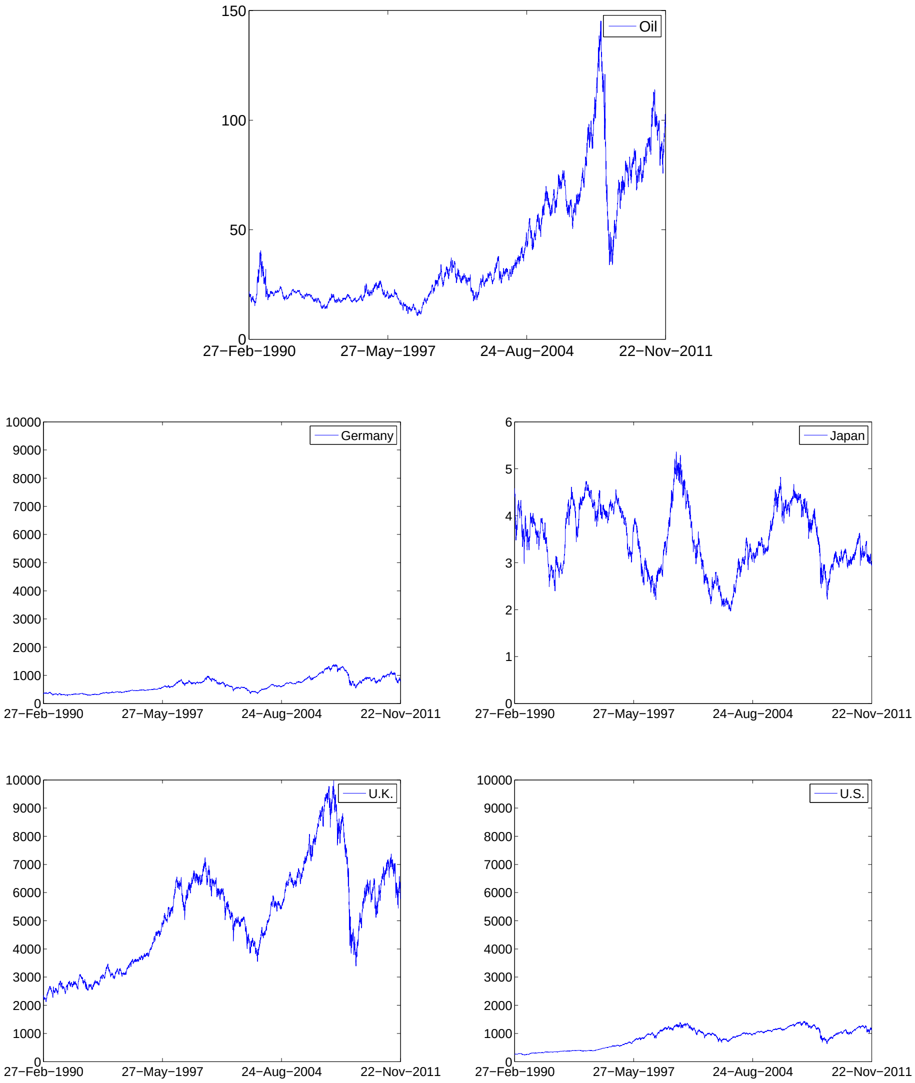


**Figure 1.** Prices of stock indexes and oil.

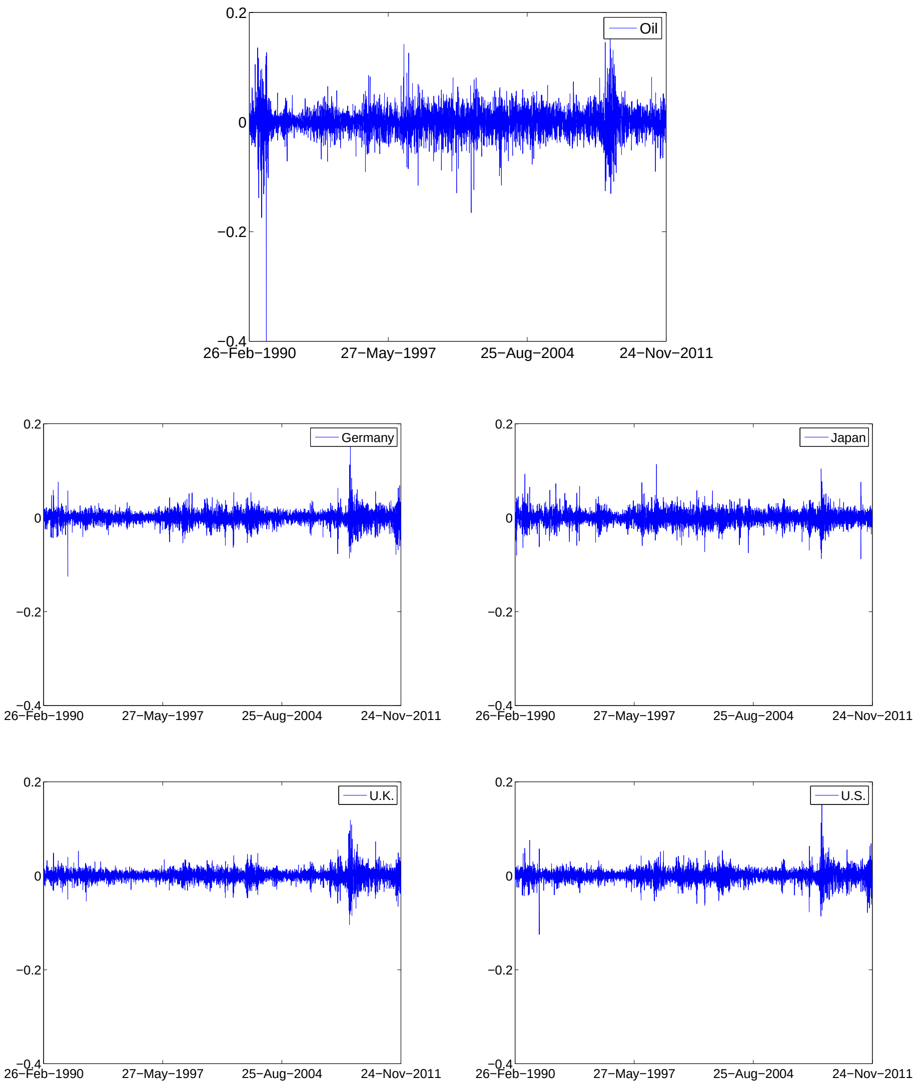


**Figure 2.** Returns of stock market indexes and oil.

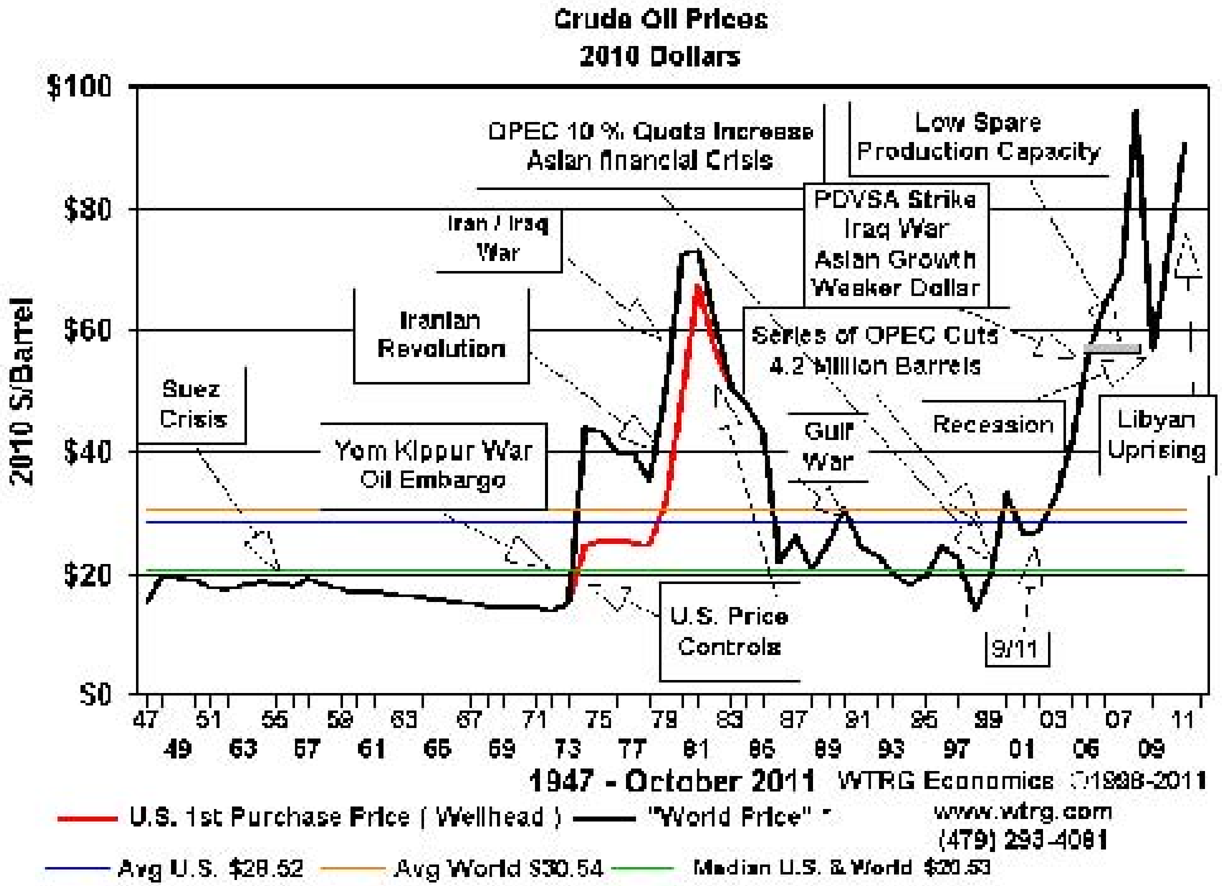


Figure 3: Evolution of oil prices together with the oil events. Source: www.wtrg.com/prices.htm.

**Table I**
**Summary statistics**

This table presents the summary statistics of the returns of stock market indexes and oil. The sample period ranges from 1990:02 till 2011:11. By column, we report the mean, the standard deviation (sd), the kurtosis, the skewness and the pvalues of the Jarque-Bera test statistics. The returns are the first differences of the logarithm of prices.

| | mean | sd | skewness | kurtosis | p_value–JB |
|---|---|---|---|---|---|
| Oil | 0.0003 | 0.0245 | -0.8990 | 20.2881 | 0.000 |
| Germany | 0.0001 | 0.0135 | -0.0549 | 12.0560 | 0.000 |
| Japan | -0.0001 | 0.0145 | 0.0528 | 7.0025 | 0.000 |
| U.K. | 0.0002 | 0.0125 | -0.1722 | 12.0906 | 0.000 |
| U.S. | 0.0003 | 0.0116 | -0.2739 | 11.6665 | 0.000 |

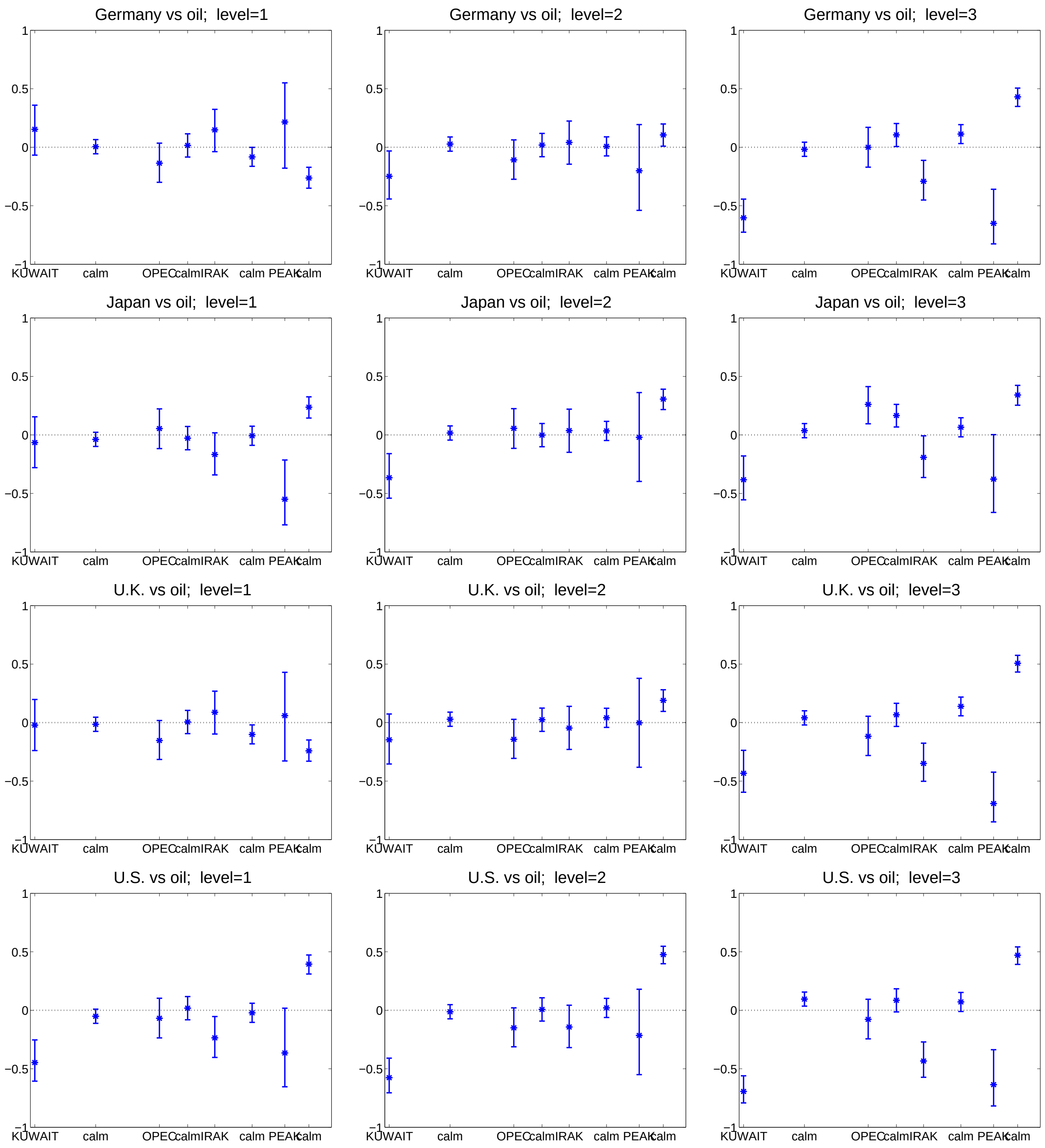


**Figure 4.** Intervals for correlations among stock markets and oil in calm/shock periods. Detail levels 1, 2 and 3.

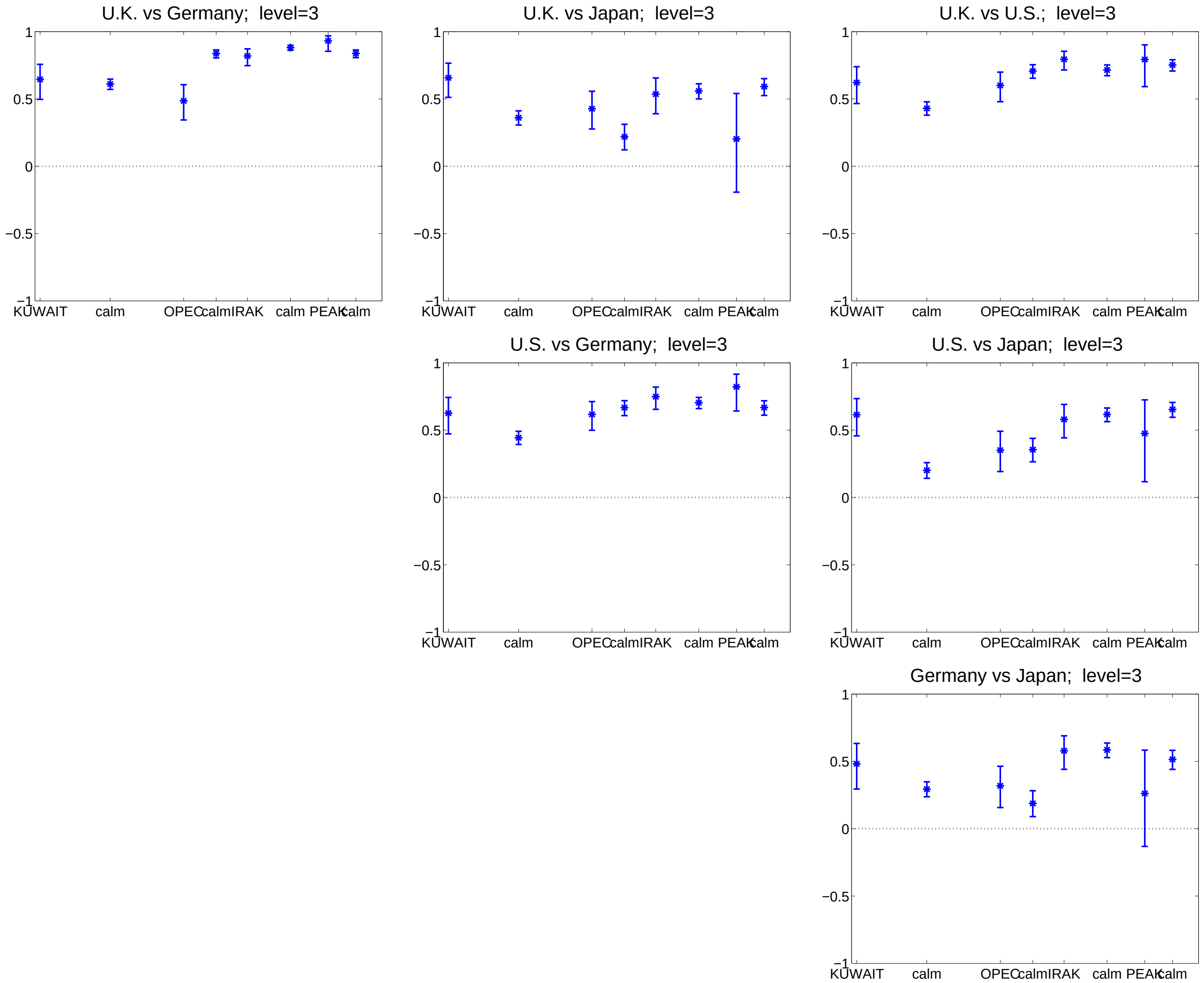


**Figure 5.** Intervals for correlations between stocks markets calm versus shock periods. Detail level 3.

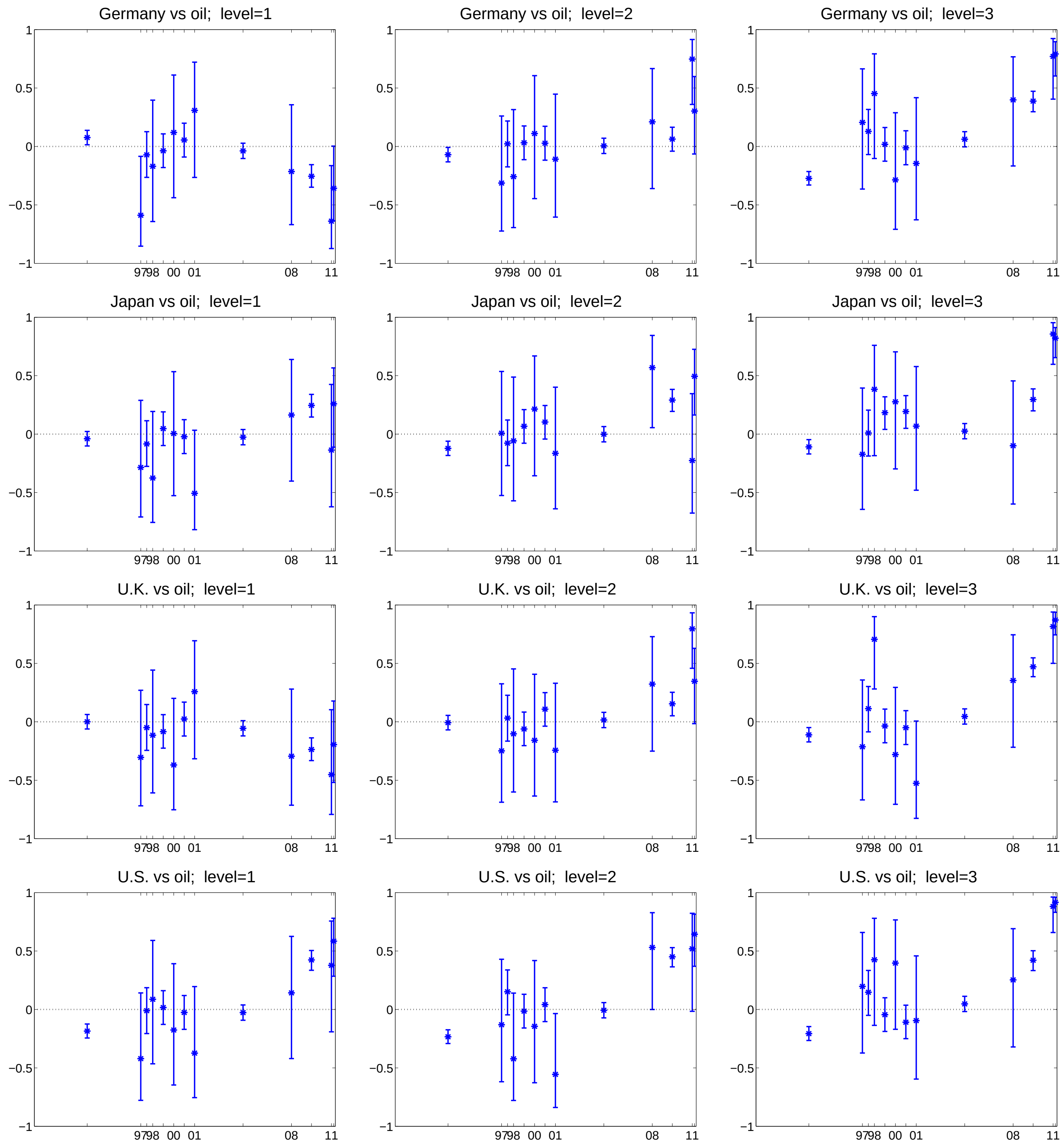


**Figure 6.** Intervals for correlations among stock markets and oil in shock and non-shock periods. Detail levels 1, 2 and 3.